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Factors Impacting the Perceived Usefulness and Behavioral Intention toward Blended Learning System in Higher Education

Zhijian Lin*

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Abstract

Purpose: This study aimed to assess the factors that impact students' perceived usefulness and behavioral intentions toward blended learning systems (BLS) in Chinese higher education. **Research design, data, and methodology:** This study adopts quantitative research methods, using Item-Objective Congruence and Pilot Tests to estimate the validity and reliability of the questionnaire. Based on various sampling methods, an electronic questionnaire was used to collect data, and Cronbach's Alpha was used to evaluate the reliability of the data. According to the proposed research model, Confirmatory Factor Analysis (CFA) was used to analyze the structural validity, and Structural Equation Modeling (SEM) was used to test the structural correlation. **Results:** It was found that the perceived usefulness of BLS was significantly affected by information quality, system quality, and collaboration quality (CBQ). Perceived usefulness, hedonic motivation, facilitating condition, and effort expectancy significantly drove behavioral intention to use BLS. **Conclusions:** This study proposed a composite research framework to analyze the influence of college students' behavior and intention to use BLS more completely and effectively. The researchers believed that improving the quality factors and external promotion conditions of BLS could improve students' PU for BLS and promote students' enthusiasm and intention to use BLS.

Keywords: Blended Learning System, Perceived Usefulness, Behavioral Intention, Higher Education, China

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Learning is acquiring knowledge, demonstration, and experience to improve or change one's cognition and skills (Anthony et al., 2019). From the viewpoint of system theory, teaching and learning are complex systems, and students achieve learning success by cultivating learning systems. The traditional learning environment is an interlinked learning system composed of teachers, classrooms, textbooks, students, courses, and conventional paper tests (Bokolo et al., 2020). Information and communication technology (ICT) has progressed greatly in recent decades. ICT can quickly process various types of information, greatly improving our work and life (Raees, 2002). In education, information and communication technologies can facilitate the education and learning process (Passey, 2006; Wang, 2008). With the development of science and technology, educational institutions are using information and communication technology to promote education development, combining traditional face-to-face teaching with online teaching resources to provide students with a more convenient learning environment and rich learning content (Wong et al., 2014).

A blended learning environment is a complete and interrelated learning environment composed of digital course materials, network tools, and physical classrooms (Owston et al., 2008). Blended learning refers to the process that students learn through the blended learning system to achieve the goal of innovative talents. The blended learning process is a mixed learning activity composed of physical interaction between teachers, students, and courses, as well as online interaction of learning systems, online resources,

1*Zhijian Lin, Ph.D. Candidate in Innovative Technology Management, Graduate School of Business and Advance Technology Management, Assumption University, Thailand. Email: 864948068@qq

and technology promotion (Bliuc et al., 2007). Blended learning was considered an educational method that combined the online education process with traditional classroom teaching methods (Rivera, 2019; Wang, 2019). Some studies defined blended learning as learning systems that use new technologies to facilitate teaching (Friesen, 2012). This study defines blended learning as a complex system of multiple related factors. This study will further study college students' perceived usefulness and behavioral intention to use the blended learning system (service).

A blended learning system (BLS) was a compound learning service system that combined the advantages of online learning and traditional classroom learning (Garrison & Kanuka, 2004; Harriman, 2004), which integrated the suitable learning system environment and technology, enhanced students' interactive experience with other learners (Singh, 2003), provided convenient and rich learning materials, implemented different synchronous and asynchronous teaching strategies, and stimulated students' active participation in the blended learning process (Lakhal et al., 2013; Okaz, 2015). The researcher agreed with the definition of blended learning proposed by Garrison and Kanuka (2004), believing that BLS was a complex system in which multiple elements of classroom learning and online learning process interact. In this study, the researcher thought that the BLS was a kind of "online + offline" learning system based on modern teaching theory, which could usefully meet the needs of learners and improve learning performance with the support of ICT.

Blended learning is increasingly gaining attention and application in higher education institutions because of its advantages over traditional and online learning methods (Bokolo et al., 2020). However, a blended learning system (BLS) involves internal and external factors, including system serviceability, information resource abundance, teacher-student interaction effect, team cooperation process, etc. The adoption of BLS by educational institutions is both an opportunity and a challenge. Therefore, there is an urgent need to study college students' perceived usefulness and use intention in adopting BLS initiatives. This paper records an experiment of college students who have participated in blended learning for one semester, aiming to study the factors influencing students' intention to use BLS, especially in blended learning environments in higher education.

2. Literature Review

2.1 Information Quality

Information quality refers to the quality of content, which is characterized by accuracy, effectiveness, relevance, and timeliness of information and other dimensions (Ahn et al., 2007; DeLone & McLean, 2003; Kim et al., 2008). Gustavsson and Wanstrom (2009) defined information quality as the ability of an information system's information content to meet learners' information needs. In e-learning systems, the most common measure of information quality is the quality of course content, which attracts learners' continuous attention by providing rich and updated course content (Lee, 2006). Information quality refers to the quality of various information contents and resources provided by information technology platforms, which can satisfy users' needs for information quality and thus have a significant impact on the perceived usefulness of the system (Chiu et al., 2011; Ramayah et al., 2010). In investigating the determinants of blended learning action, Mirabolghasemi et al. (2021) defined information quality as the quality of learning resources uploaded to a learning management system and assessed by learners.

When the e-learning system provides comprehensive learning content that meets learners' expectations and updates quickly, the high-quality information will make learners feel satisfied with the e-learning system, thus motivating learners to continue to use the e-learning system (Lee, 2006; Lee et al., 2009; Liu et al., 2010). Several previous studies (Ahn et al., 2007; Cheng, 2012; Venkatesh & Davis, 1996) showed that information quality had a primary positive influence on perceived usefulness and ease of use, and higher levels of information quality satisfy users with higher perceived usefulness. Referring to stated studies, therefore, conclude the hypothesis:

H1: Information quality has a significant impact on perceived usefulness.

2.2 System Quality

System quality reflects the characteristics of online response speed, stability, ease of use, and accuracy of information system (DeLone & McLean, 2003). Wang and Wang (2009) believed that ease of control, flexibility, functional richness, applicability, accessibility, and interactivity were important features of system quality. Cheng (2012) considered that system quality consists of information systems' functionality, interactivity, responsiveness, and user-friendliness. Chopra et al. (2019) believe that the system quality of e-learning websites refers to the system response measure that learners can easily access course content or learning materials. According to the research on the system quality of e-learning portal websites, Dobbs (2000) and Fabianic (2002) both found that functional navigation, presentation of resources on the website, website content searchability, website response speed, and responsiveness, website interface design, personalized service, and other dimensions are important dimensions of system quality. According to many previous views, the improvement of system quality enables the user to perceive the functional performance of the system and the usefulness of the system, thus increasing the intention and decision to use the system in the future (Kim et al., 2008; Polites et al., 2012; Shin, 2015).

Previous studies have shown that higher system quality leads to higher user satisfaction and has a positive impact on learners' intention to use information systems (Krishnasamy et al., 2020; Sharma et al., 2017; Tajuddin et al., 2013). According to many empirical studies, when e-learning systems provide them with appropriate system functionality, timely responses, and effective connections with teachers and other learners through the system, they are likely to feel that high-quality systems are very consistent with predictors of perceived usefulness (Cho et al., 2009; Lee et al., 2009; Pituch & Lee, 2006). High system quality has been shown to increase system functionality and efficiency, resulting in a higher level of system usefulness perceived by users. The relevant corollaries and hypotheses are explained in further detail below.

H2: System quality has a significant impact on perceived usefulness.

2.3 Instructor Quality

Instructor quality was defined as the degree to which learners perceive the teacher's instructional attitude, including timely response to learning problems, perception of a positive teaching attitude and style, and access to effective interaction and valuable help (Choi et al., 2007; Lee et al., 2009). Whether it is traditional or online learning, the role of the instructor has always been regarded as one of the key people and principal factors determining the learner's success in this process. In the e-learning system, the high-quality instructor can demonstrate an interactive teaching style, promote effective communication between learners and teachers, enable learners to be enthusiastically immersed in this interaction, affect students' attitude towards e-learning, and experience learning fun (Abbas, 2016; Choi et al., 2007; Ozkan & Koseler, 2009). High-quality instructors must provide appropriate knowledge and motivate students to use e-learning technology to increase students' acceptance of the e-learning system because the implementation of technology was an important reason for the success of e-learning (Alrousan et al., 2022; Kisanjara et al., 2019).

Instructors are the basis of the social communication relationship between the various elements of the university, who use teaching methods and technology to serve students and promote the growth of students. A high level of instructor quality means that learners perceive the teacher's friendly handling and care for learners and receive timely responses to meet learning needs, which gives learners confidence that the system is useful (Lee et al., 2009; Sun et al., 2008). Many previous studies have found that instructor characteristics significantly impact the perceived usefulness of adopting e-learning systems (Hadullo et al., 2017; Lee et al., 2009; Yiong et al., 2008). In line with previous literature, the following hypothesis is proposed:

H3: Instructor quality has a significant impact on perceived usefulness.

2.4 Collaboration Quality

The collaborative quality of learners was defined as the quality of interaction and assistance between learners and others during the learning communication process (Cheng, 2022). Collaboration quality based on e-learning platform refers to the degree to which learners feel the interaction with other system elements, including the interaction of technical knowledge and system functions, and easy communication with other learners on the platform to improve the effectiveness of information sharing and learning efficiency (Chen et al., 2018; Cidral et al., 2018; Kuo et al., 2014). Collaborative learning environments encourage learners to interact to construct new extensible knowledge rather than simply repeating previous knowledge content (Stahl et al., 2006). Some meta-analyses have demonstrated that collaborative learning promotes individual learning and collaborative achievement (Pai et al., 2015). If supported by information technology and systems, collaborative activities can further enhance learning (Chen et al., 2018). In an e-learning environment, the degree of collaboration and interaction between learners facilitates extensive knowledge sharing. It promotes the improvement of individual learners' knowledge, which is necessary for the success of e-learning (Cheng, 2022).

Strau and Rummel (2020) showed that collaborative learning is an effective learning activity, and improving the quality of cooperative learning benefits learners' perceived usefulness of the e-learning system. Similarly, much empirical research showed that if learners are highly interactive with other learners through the use of e-learning, they are more likely to perceive the usefulness of the system and will have the intention to be more actively involved and immersed in this use of e-learning (Chen et al., 2009; Choi et al., 2007; Molinillo et al., 2018). Based on the above literature review, the following hypotheses are similarly proposed:

H4: Collaboration quality has a significant impact on perceived usefulness.

2.5 Perceived Usefulness

Davis et al. (1989) believed that perceived usefulness was the degree to which a person expected to improve job performance through a particular technical approach. In the

Internet environment, the perceived usefulness of information systems was defined as the degree to which individuals believe that new technologies can improve their task performance (Lee, 2006). For example, in the e-learning context, perceived usefulness was defined as the degree to which students believe academic performance can be improved through e-learning technologies and services (Lee et al., 2009). Many empirical studies (Gefen et al., 2003; Lee, 2006; Ong et al., 2004; Venkatesh & Davis, 2000) have shown that perceived usefulness was the primary factor affecting the use of information technology and found a significant association between perceived usefulness and the adoption of new technologies or services in different system contexts including e-banking, e-commerce, e-government, e-learning, etc. Cheng (2012) pointed out that the perceived usefulness of e-learning would affect the intention to use e-learning systems, and Alsabawy et al. (2016) believed that the perceived usefulness of e-learning is affected by the foundation of information technology, the quality of the system, and the quality of information.

In the TAM model, behavioral intention is determined by users' attitudes and perceptions of the system's usefulness, and the user's behavioral intention has a decisive relationship with the actual use of the system (Davis et al., 1989). Abdekhoda et al. (2020) show a direct and significant correlation between perceived usefulness and behavioral intention to adopt flipped classrooms. Therefore, the following hypothesis was formed:

H5: Perceived usefulness has a significant impact on behavioral intention.

2.6 Hedonic Motivation

The hedonic motivation was considered an intrinsic property of pleasant feeling, which was the result of the fun, enjoyment, and playful experience felt during the use of technology (Brown & Venkatesh, 2005). Venkatesh et al. (2012) argued that hedonic motivation refers to the pleasure or enjoyment obtained from using technology and confirmed that hedonic motivation was a key influencing factor in the intention to use technology. The hedonic motivation was a new structural variable added to UTAUT2 that was defined to measure the user's enjoyment of using a system or service. Nguyen et al. (2014) confirmed that hedonic motivation was one of the important intrinsic situational factors in predicting students' behavioral intention to use e-learning and mobile learning systems. According to the self-determination theory, El-Masri and Tarhini (2017) believed that when students were interested in e-learning systems and enjoyed using e-learning, they would be intrinsically motivated to participate actively in e-learning.

Brown and Venkatesh (2005) summarized many empirical results showing that the hedonic motivation and pleasure generated by the perceived effectiveness of using technology or service play an important role in determining the adoption of new technology. Moorthy et al. (2019) considered that hedonic motivation significantly positively impacted the students' behavioral intention to accept mobile learning. Therefore, a hypothesis on the relationship between hedonic motivation and behavioral intention of blended learning is proposed:

H6: Hedonic motivation has a significant impact on behavioral intention.

2.7 Facilitating conditions

Facilitating conditions were regarded as the extent to which individuals believed that objective organizational and technical infrastructure conditions supported the use of the system (Venkatesh et al., 2003). El-Masri and Tarhini (2017) argued that facilitating conditions were an external environment that enabled students to access electronic system resources easily. Sattari et al. (2017) underscored the importance of facilitating conditions as external conditions and argued that facilitating conditions positively impact the behavioral intention to accept e-learning systems. Similarly, Samsudeen and Mohamed (2019) pointed out that facilitating conditions in an e-learning system was an environment supported by technical and organizational infrastructure that can help college students use e-learning. According to previous research results, facilitating conditions provided technical conditions to facilitate users to accept blended learning, and there was a positive correlation between facilitating conditions and users' behavioral intentions to accept a blended learning system (Abu-Gharrah & Aljaafreh, 2021; Lu et al., 2020; Wu & Liu, 2013).

Azizi et al. (2020) used the UTAUT2 model to study the factors affecting the acceptance of blended learning in medical education. They found that facilitating conditions significantly affected the students' behavioral intention to use blended learning. Rudhumbu (2022) argued that students who believed their institutions had sufficient and applicable technical and organizational infrastructure would develop behavioral intentions to use a blended learning system. Therefore, the following hypothesis is:

H7: Facilitating conditions have a significant impact on behavioral intention.

2.8 Effort Expectancy

Effort expectancy was defined as the degree of perceived ease of access and operational simplicity of a system (Venkatesh et al., 2003), which was a perceived structure variable like perceived ease of use in a technology acceptance model. Many empirical studies argued that if learners found it easier to use e-learning, they would be willing to adopt it. Based on this premise, El-Masri and Tarhini (2017) found that effort expectation is an important predictor of learners' intention to use e-learning. Perera and Abeysekera (2022) also believed that effort expectancy was the perception of a person (learner) to use the information system without any extra effort, affecting the learner's behavioral intention to use e-learning. Based on the UTAUT2 theory, Azizi et al. (2020) explored the influencing factors of blended learning acceptance in medical education. They found that effort expectancy significantly positively impacted students' behavioral intention to use blended learning. Abdekhoda et al. (2016) showed that effort expectancy was one of the factors that predicted the behavioral intention of using e-learning systems.

Marandu et al. (2023) believed that the effort expectancy among the factors influencing continuous online learning in the post-COVID-19 era was significantly positively correlated with the intentions to use online learning systems, but Twum et al. (2022) found an insignificant correlation between effort expectancy and intention to use E-learning. Based on previous evidence, this study hypothesizes the following:

H8: Effort expectancy has a significant impact on Behavioral Intention.

2.9 Behavioral Intention

Behavioral intention refers to the subjective probability of a user performing a particular action. If a person intends to follow a product or service, they are more likely to become a practical user. In the technology acceptance model study, Davis et al. (1989) argued that behavioral intention was the sense that the user was ready to participate in designated tasks or perform a certain behavior. According to many empirical studies, behavioral intention best predicts a person's actual behavior (Zhang et al., 2008). Kim and Niehm (2009) also argued in their research that behavioral intention was an extremely important factor in predicting users' actual behavior. Many previous studies have emphasized that the important factor of individual acceptance of blended learning system was the behavioral intention of blended learning, and there was a significant correlation between behavioral intention and acceptance of blended learning (Abu-Gharrah & Aljaafreh, 2021; Azizi et al., 2020; Huang & Kao, 2015).

3. Research Methods and Materials

3.1 Research Framework

The research model proposed by the researchers is based on three core theoretical models, which are the Technology Acceptance Model (TAM) designed by Davis et al. (1989), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) proposed by Venkatesh et al. (2012), and the updated DeLone and McLean information system success model (DMIS) proposed by DeLone and McLean (2003). Based on the hybrid integrated DMIS, TAM, and UTAUT2 models, this study proposes a comprehensive model to test the extended quality factor of BLS as the antecedent of students' perceived usefulness of the system and further study the internal and external factors that affect their behavioral intention to use BLS.

The conceptual framework of this paper also draws on four previous empirical studies of theoretical framework. The first theoretical framework was based on Lee (2006) empirical study on the factors that influence the adoption of e-learning systems, which proposed an extended model based on TAM for external variables impacting perceived usefulness and behavioral intention. The second theoretical framework was conducted by Cheng (2014), which was integrated from the expectation confirmation model (ECM) and DMIS theory to discuss the extended quality and process impacting toward perceived usefulness in blended e-learning systems and explore the factors of continuance intention. The third theoretical framework was conducted by Cheng (2022), which, based on the DMIS model, proposed five external factors, namely knowledge quality, system quality, interface design quality, learner-instructor interaction quality, and collaboration quality, impacting users' perception of the usefulness of the learning system. The fourth theoretical framework was carried out by Rudhumbu (2022), which applied UTAUT2 proposed four major constructs, namely performance expectation, effort expectancy, social influence, facilitating conditions, and three expanded structures, namely hedonic motivation, price value, and habit to predict blended learning acceptance among students at the University of Zimbabwe. The research conceptual framework of this study is shown in Figure 1.

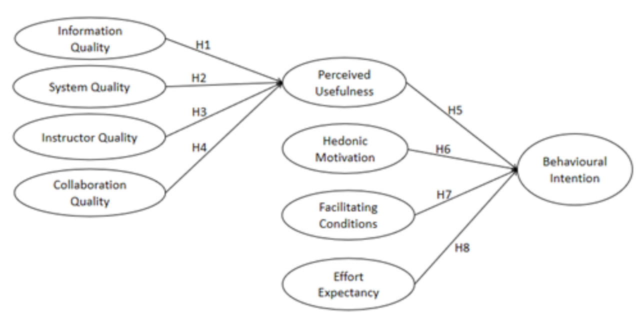

Figure 1: Conceptual Framework

H1: Information quality has a significant impact on perceived usefulness.
H2: System quality has a significant impact on perceived usefulness.
H3: Instructor quality has a significant impact on perceived usefulness.
H4: Collaboration quality has a significant impact on perceived usefulness.
H5: Perceived usefulness has a significant impact on Behavioral Intention.
H6: Hedonic motivation has a significant impact on behavioral intention.
H7: Facilitating conditions have a significant impact on behavioral intention.
H8: Effort expectancy has a significant impact on behavioral intention.

3.2 Research Methodology

The methodology of this study included target population, sampling/questionnaires, data collection procedures, confirmatory factor analysis (CFA), goodness of fits or model fits, and structural equation model (SEM) for hypothesis testing. This study uses empirical and quantitative analysis methods to explore the factors that affect the behavior intention of college students using a blended learning system. The researcher used the Item-Objective Congruence to test the content validity and Cronbach's Alpha to test the reliability. This questionnaire was produced by Questionnaire Star online, which is convenient for data distribution and collection. After collecting the data, the researcher used JAMOVI and AMOS statistical tools to analyze and process the sample data. The structural equation model (SEM) will be used in this study to verify the structure of the relationship between variables in the conceptual framework.

3.3 Population and Sample Size

Hair et al. (2010) defined the target population as a group of people with the same data description associated with the research plan, who, as respondents, collected characteristic data for research purposes. The target population of this study is undergraduates who have participated in a semester of blended learning at Zhanjiang University of Science and Technology. According to the online statistical program Soper (2006) provided, the recommended minimum sample size was 460 from the latent variables number of 9 and the observed variables number of 37 at the probability level of 0.05. Therefore, the questionnaires are distributed and screened for valid responses at 500.

3.4 Sampling Technique

In this study, the researcher used purposive sampling, stratification random sampling, and purposive convenient sampling to collect data, and adopted stepwise sampling procedures to ensure that the data set was consistent with the research objectives. This study adopts the method of purposive sampling to select five major secondary schools of Zhanjiang University of Science and Technology, as shown in Table 1. The researcher uses proportional stratified sampling technology to calculate the number of target respondents in each group to ensure the total sample size of 500 samples.

Table 1: Sample Units and Sample Size

Five Mainly Secondary Colleges	Population Size	Proportional Sample Size
School of Management	2,850	114
School of Economics and Finance	2,420	96
School of Fine Arts and Design	2,250	90
School of Intelligent Manufacturing	3,400	136
School of Architecture Engineering	1,600	64
Total	12,520	500

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic profile of 500 respondents is presented in Table 2. The respondents consist of 281 males and 219 females, which represent 56.2%, and 43.8%, respectively. From the perspective of age, respondents are mainly between 20 and 23 years old, with 20-21 years old accounting for the largest proportion, accounting for 47.4%, followed by 22-23 years old accounting for 36.6%, 18-19 years old accounting for 15.6%, and more than 24 years old accounting for 0.4%. For the year of study, freshman accounts for 12.4%, sophomore accounts for 35.0%, junior accounts for 30.8%, and senior accounts for 21.8%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	281	56.2%
	Female	219	43.8%
Age	18-19 years old	78	15.6%
	20-21 years old	237	47.4%
	22-23 years old	183	36.6%
	More than 24 years old	2	0.4%
Year of Study	Freshman	62	12.4%
	Sophomore	175	35.0%
	Junior	154	30.8%
	Senior	109	21.8%

4.2 Confirmatory Factor Analysis (CFA)

Construct validity measurement has been commonly used to produce statistical results involving convergent and discriminant validity (Straub, 1989). Confirmatory factor analysis (CFA) was a widely used construct validity statistical method in variable research (Goodwin & Leech, 2003). Convergent validity can be measured by Cronbach's Alpha reliability, factor loading, composite reliability, and average variance extracted (Pallant, 2010). Discriminant validity was used to test divergence validity with related constructs (Fornell & Larcker, 1981). The researcher used SPSS and AMOS to build a measurement model for construct validity analysis.

Factor loading over 0.50 exceeds significance based on guidelines Hair et al. (2006) recommended. In this study, the factor loading of all items was above 0.50, and most of them were greater than 0.70, ranging from 0.605 to 0.943, as shown in Table 3. Fornell and Larcker (1981) recommend that the composite reliability above 0.7 and the average variance extracted greater than the cut-off point 0.4 were acceptable values. Table 3 shows that all estimates are significant for CR values over 0.7 and AVE values over 0.5.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Information quality (IFQ)	Cheng (2014)	4	0.857	0.605-0.943	0.858	0.610
System quality (SQ)	Cheng (2014)	4	0.838	0.707-0.867	0.840	0.569
Instructor quality (ISQ)	Rughoobur and Hosanoo (2021)	5	0.845	0.657-0.797	0.847	0.526
Collaboration quality (CBQ)	Cheng (2022)	4	0.795	0.641-0.769	0.798	0.499
Perceived usefulness (PU)	Abdekhoda et al. (2020)	6	0.856	0.621-0.763	0.858	0.503
Hedonic motivation (HM)	Rudhumbu (2022)	3	0.816	0.732-0.832	0.820	0.603
Facilitating conditions (FC)	Rudhumbu (2022)	4	0.815	0.666-0.799	0.821	0.536
Effort expectancy (EE)	Rudhumbu (2022)	4	0.845	0.702-0.809	0.847	0.580
Behavioral intention (BI)	Rudhumbu (2022)	3	0.767	0.681-0.830	0.777	0.540

According to Table 4, the CFA statistical values of CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA are all greater than acceptable values, which proves the measurement model's goodness of fit.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012;)	2.362
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.871
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.847
NFI	≥ 0.80 (Wu & Wang, 2006)	0.842
CFI	≥ 0.80 (Bentler, 1990)	0.901
TLI	≥ 0.80 (Sharma et al., 2005)	0.889
RMSEA	< 0.08 (Pedroso et al., 2016)	0.052
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

According to Table 5, the value of discriminant validity is larger than all inter-construct/factor correlations, so the discriminant validity is recognized.

Table 5: Discriminant Validity

	IFQ	SQ	ISQ	CBQ	PU	HM	FC	EE	BI
IFQ	**0.781**								
SQ	0.296	**0.754**							
ISQ	0.193	0.277	**0.725**						
CBQ	0.180	0.215	0.184	**0.706**					
PU	0.280	0.225	0.159	0.322	**0.709**				
HM	0.194	0.190	0.150	0.175	0.207	**0.777**			
FC	0.216	0.240	0.156	0.142	0.128	0.210	**0.732**		
EE	0.171	0.243	0.241	0.200	0.240	0.218	0.201	**0.762**	
BI	0.216	0.351	0.282	0.307	0.343	0.288	0.334	0.354	**0.735**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The structural equation model (SEM) is a comprehensive confirmatory method of theoretical models, which can be combined with statistical techniques and theoretical hypotheses to evaluate the underlying relationships between variables. According to Klem (2000), the structural equation model (SEM) is a multivariate statistical technique that can verify causality between potential variables through factor analysis. SEM was also used to describe the verification of hypotheses based on the construction of models (Hoyle, 2011).

In Table 6, the statistical values are CMIN/DF = 2.328, GFI = 0.850, AGFI = 0.830, NFI=0.837, CFI = 0.900, TLI = 0.892, RMSEA = 0.052. All these fitting indexes are greater than the acceptable values, so they affirmed the structural model fitness.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012;)	2.328
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.850
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.830
NFI	≥ 0.80 (Wu & Wang, 2006)	0.837
CFI	≥ 0.80 (Bentler, 1990)	0.900
TLI	≥ 0.80 (Sharma et al., 2005)	0.892
RMSEA	< 0.08 (Pedroso et al., 2016)	0.052
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

The significance of correlation among the independent and dependent variables proposed in the hypothesis was determined by regression or standardized path coefficients (Huang & Duangekanong, 2022). As shown in Table 7, the study proposed eight hypotheses, seven of which were supported. The perceived usefulness of blended learning systems was significantly impacted by information quality, system quality, and collaboration quality. The behavioral intention to use a blended learning system was strongly driven by perceived usefulness, effort expectancy, facilitating condition, and hedonic motivation.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: IFQ→PU	0.188	3.921*	Supported
H2: SQ→PU	0.140	2.832*	Supported
H3: ISQ→PU	0.066	1.359	Not Supported
H4: CBQ→PU	0.326	6.067*	Supported
H5: PU→BI	0.272	5.132*	Supported
H6: HM→BI	0.187	3.588*	Supported
H7: FC→BI	0.296	5.338*	Supported
H8: EE→BI	0.288	5.311*	Supported

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$
Source: Created by the author

As shown in Table 7, the standardized path coefficient of H1 is 0.188, and the t-value is 3.921, indicating that IFQ significantly impacts the PU of blended learning systems (BLS). SQ significantly impacted PU with a standardized path coefficient of 0.140 and a t-value of 2.832 in H2. CBQ has the most significant impact on PU, with a standardized path coefficient of 0.326 and a t-value of 6.067 in H4. The research hypothesis H1, H2, and H4 of quality factors affecting PU are supportive.

However, the Path relationship of ISQ and PU has a standardized path coefficient of 0.066 and a t-value of 1.359 in H3. The standardized path value does not prove that ISQ has a significant impact on PU of BLS, so H3 is not supported. Many previous empirical studies held that when teachers can handle learners' online learning friendly and respond to learners' needs promptly through an e-learning system, learners will think the system is useful (Choi et al., 2007; Lee et al., 2009; Ozkan & Koseler, 2009). The measurement of H3 in this study is inconsistent with previous studies. The reasons for the failure to support H3 may be the limitation of the operation function of teacher-student interaction on the online platform, the inability of teachers to respond to learners' needs promptly for personal reasons, and the incoherent and insufficiently focused interaction between teachers and students on the online learning platform, which affects the instructor quality.

As shown in Table 7, FC has the Strongest impact on behavioral intention (BI) to use BLS. The path relationship of FC and BI has a standardized path coefficient of 0.296 and a t-value of 5.338 in H7. Respectively, the EE of BLS significantly impacted BI's use of BLS with a standardized path coefficient of 0.288 and t-value of 5.311 in H8. The standardized path coefficient of H5 was 0.272, and the t-value was 5.132, indicating that PU significantly impacts BI. In addition, HM significantly impacted BI with a standardized path coefficient of 0.187 and a t-value of 3.588 in H6. Significantly, the research hypothesis H5, H6, H7 and H8 of BI to use BLS are supportive.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study focused on the comprehensive factors that impact college students' perceived usefulness and behavioral intention to blended learning systems (BLS). The researchers proposed a composite conceptual framework with eight hypotheses to examine the factors influencing behavioral intention. According to the collected data, CFA was used to measure the conceptual model's validity and reliability. SEM was used to test the correlation among factors affecting college students' behavioral intention to use BLS. The research described the findings as follows.

First, this study proposed a hybrid research model based on the previous three core theoretical models, which integrates the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the updated DeLone and McLean information system success model (DMIS). The researchers verified the structural validity of the composite research model by CFA and verified the hypothesis of all important paths of the research model by SEM. The model more comprehensively supported analyzing factors affecting college students' intention to use BLS.

Second, this study extends DeLone and McLean's success model (DMIS) by adding ISQ and CBQ as key quality factors affecting students' perceived usefulness of BLS. Three quality determinants, IFQ, SQ, and CBQ, were found to be belief antecedents affecting college students' intention to use BLS, with CBQ having the strongest influence.

Third, this study integrates TAM and UTAUT2 models to consider the external quality factors and intrinsic motivators that affect college students' behavioral intention to use BLS in order to obtain a more complete and robust analysis. It is found that PU, HM, FC, and EE significantly influence college students' intention to use BLS.

5.2 Recommendation

This study explains in detail the factors that affect the behavioral intention of college students to use BLS. This study provides teaching managers or course designers with the ability to identify the variables that affect the willingness of college students to use BLS, which is helpful to the development, optimization, and utilization of BLS. In this study, PU is significantly affected by IFQ, SQ, and CBQ, so it is suggested that universities or educational institutions should continuously enrich course materials when carrying out BLS, timely update the knowledge corresponding to offline courses, and improve the multifunctional characteristics of the system to improve the system response. CBQ is the strongest factor affecting PU, and college students strongly believe in collaborative learning. The system's online interaction and discussion function should be enhanced to provide more opportunities for offline collaboration tasks and interaction between teachers and students. However, this study found that ISQ had no significant effect on PU. This is contrary to the conclusions of previous studies, which require further and longer investigation statistics.

In this study, BI is significantly driven by PU, FC, HM, and EE. Universities or educational institutions should improve the basic network conditions, provide a variety of equipment required by BL, optimize BLS to make it more convenient and easier to use, and pay attention to the combination of online and offline content so as to achieve online convenience and experience the actual interaction offline. This can enhance students' belief in the usefulness of BLS and motivate learners to learn more actively.

5.3 Limitation and Further Study

This study has some limitations, and the following suggestions are worthy of further research. First, this study's population and sample survey scope are limited to students majoring in engineering, business, and liberal arts in one university. Further research will expand the scope of the survey population and conduct a wider sample survey and data statistics from multiple universities in different regions to obtain a more objective analysis. Second, Cheng (2014) believed that if teachers identify the obstacles and needs of learners in blended e-learning, carry out interactive and customized teaching styles, and help students participate in active learning, it would promote a close connection between teachers and students. This study found that ISQ had no significant effect on PU, which may be the cause of insufficient teacher guidance. The follow-up research will improve the quality and task requirements of teacher guidance, meet students' needs for teacher guidance in the BLS process, and further study the impact of ISQ on PU. Third, the successful implementation of BLS will also be affected by the length of continuous learning time. In further research, we will investigate the factors influencing learners' behavioral intention on BLS for learners who continue to conduct BL for over one year.

References

Abbas, T. (2016). Social factors affecting students' acceptance of e-learning environments in developing and developed countries: a structural equation modeling approach. *Journal of Hospitality & Tourism Technology, 7*(2), 200-212. https://doi.org/10.1108/jhtt-11-2015-0042

Abdekhoda, M., Dehnad, A., Mirsaeed, S., & Gavgani, V. (2016). Factors influencing the adoption of e-learning in Tabriz University of Medical Sciences. *Medical Journal of the Islamic Republic of Iran, 30,* 457.

Abdekhoda, M., Maserat, E., & Ranjbaran, F. (2020). A conceptual model of flipped classroom adoption in medical higher education. *Interactive Technology and Smart Education, 17*(4), 393-401. https://doi.org/10.1108/itse-09-2019-0058

Abu-Gharrah, A., & Aljaafreh, A. (2021). Why students use social networks for education: Extension of UTAUT2. *Journal of Technology and Science Education, 11*(1), 53-66. https://doi.org/10.3926/jotse.1081

Ahn, T., Ryu, S., & Han, I. (2007). The impact of web quality and playfulness on user acceptance of online retailing. *Information & Management, 44*(3), 263-275. https://doi.org/10.1016/j.im.2006.12.008

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of The Technology Acceptance Model in Context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4), 429-444. https://doi.org/10.5901/mjss.2015.v6n4s1p268

Alrousan, M., AlMadadha, A., AlKhasawneh, M., & Adel Tweissi, A. (2022). Determinants of virtual classroom adoption in jordan: the case of princess sumaya university for technology. *Interactive technology and smart education, 19*(2), 121-144. https://doi.org/10.1108/itse-09-2020-0211

Alsabawy, A. Y., Cater-Steel, A., & Soar, J. (2016). Determinants of perceived usefulness of e-learning systems. *Computers in Human Behaviour, 64,* 843-858. https://doi.org/10.1016/j.chb.2016.07.065

Anthony, B., Kamaludin, A., Romli, A., Raffei, A. F. M., Abdullah, A., Ming, G. L., Nurbiha, A. S., Shukri, M., & Baba, S. (2019). Exploring the role of blended learning for teaching and learning effectiveness in institutions of higher learning: an empirical investigation. *Education and Information Technologies, 24*(6), 3433-3466.

Awang, Z. (2012). *Structural equation modeling using AMOS graphic* (1st ed.). Penerbit Universiti Teknologi MARA.

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors affecting the acceptance of blended learning in medical education: application of UTAUT2 model. *BMC Medical Education, 20*(367), 1-9. https://doi.org/10.1186/s12909-020-02302-2

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bliuc, A. M., Goodyear, P., & Ellis, R. A. (2007). Research focus and methodological choices in studies into students' experiences of blended learning in higher education. *The Internet and Higher Education, 10*(4), 231-244. https://doi.org/10.1016/j.iheduc.2007.08.001

Bokolo, A., Jr., Kamaludin, A., Romli, A., Mat Raffei, A., ALe Phon, D., Abdullah, A., Ming, G. L., Nurbiha, A. S., Shukri, M., & Baba, S. (2020). A managerial perspective on institutions' administration readiness to diffuse blended learning in higher education: Concept and evidence. *Journal of Research on Technology in Education, 52*(1), 37-64.

Brown, S., & Venkatesh, V. (2005). Model of adoption of technology in households: A baseline model test and extension incorporating household life cycle. *MIS Quarterly, 29*(3), 399-426. https://doi.org/10.2307/25148690

Chen, C. C., Lee, C. H., & Hsiao, K. L. (2018). Comparing the determinants of non-MOOC and MOOC continuance intention in Taiwan: effects of interactivity and openness. *Library Hi Tech, 36*(4), 705-719. https://doi.org/10.1108/lht-11-2016-0129

Chen, S. W., Stocker, J., Wang, R. H., Chung, Y. C., & Chen, M. F. (2009). Evaluation of self-regulatory online learning in a blended course for post-registration nursing students in Taiwan. *Nurse Education Today, 29*(7), 704-709. https://doi.org/10.1016/j.nedt.2009.03.002

Cheng, Y. M. (2012). Effects of quality antecedents on e-learning acceptance. *Internet Research, 22*(3), 361-390. https://doi.org/10.1108/10662241211235699

Cheng, Y. M. (2014). Extending the expectation-confirmation model with quality and flow to explore nurses continued blended e-learning intention. Information technology & people, 27(3), 230-258.

Cheng, Y. M. (2022). Which quality determinants cause MOOCs continuance intention? A hybrid extending the expectation-confirmation model with learning engagement and information systems success. *Library Hi Tech, 41*(6), 1748-1780.

Chiu, C. M., Wang, E. T., Shih, F. J., & Fan, Y. W. (2011). Understanding knowledge sharing in virtual communities: an integration of expectancy disconfirmation and justice theories. *Online Information Review, 35*(1), 134-153. https://doi.org/10.1108/14684521111113623

Cho, V., Cheng, T., & Lai, W. (2009). The role of perceived user-interface design in continued usage intention of self-paced e-learning tools. *Computers & Education, 53*(2), 216-227. https://doi.org/10.1016/j.compedu.2009.01.014

Choi, D. H., Kim, J., & Kim, S. H. (2007). ERP training with a web-based electronic learning system: the flow theory perspective. *International Journal of Human-Computer Studies, 65*(3), 223-243. https://doi.org/10.1016/j.ijhcs.2006.10.002

Chopra, G., Madan, P., Jaisingh, P., & Bhaskar, P. (2019). Effectiveness of e-learning portal from students' perspective: a structural equation model (sem) approach. *Interactive Technology and Smart Education, 16*(2), 94-116. https://doi.org/10.1108/itse-05-2018-0027

Cidral, W. A., Oliveira, T., Felice, M. D., & Aparicio, M. (2018). E-learning success determinants: Brazilian empirical study. *Computers and Education, 122,* 273-290. https://doi.org/10.1016/j.compedu.2017.12.001

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003. https://doi.org/10.1287/mnsc.35.8.982

DeLone, W. H., & McLean, E. R. (2003). Information systems success: The quest for the dependent variable. *Information Systems Research, 12*(1), 60-95.

Dobbs, K. (2000). Who's in charge of e-learning?. *Training, 37*(6), 54-58.

El-Masri, M., & Tarhini, A. (2017). Factors affecting the adoption of E-learning systems in Qatar and USA: extending the unified theory of acceptance and use of technology 2 (UTAUT2). *Educational Technology Research and Development, 65*(3), 743-763. https://doi.org/10.1007/s11423-017-9526-1

Fabianic, D. (2002). Online instruction and site assessment. *Criminal Justice Education, 13*(1), 173-186. https://doi.org/10.1080/10511250200085401

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Marketing Research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Friesen, N. (2012, August 12). *Defining blended learning. Learning spaces.* https://www.normfriesen.info/papers/Defining_Blended_Learning_NF.pdf

Garrison, D. R., & Kanuka, H. (2004). Blended learning: *Uncovering its transformative potential. Internet and Higher Education, 7*(2), 95-105. https://doi.org/10.1016/j.iheduc.2004.02.001

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: an integrated mode. *Management Information Systems Quarterly, 27*(1), 51-90. https://doi.org/10.2307/30036519

Goodwin, L. D., & Leech, N. L. (2003). The meaning of validity in the New Standards for Educational and Psychological Testing: Implications for measurement courses. *Measurement and Evaluation in Counseling and Development, 36*(3), 181-191. https://doi.org/10.1080/07481756.2003.11909741

Gustavsson, M., & Wanstrom, C. (2009). Assessing information quality in manufacturing planning and control processes. *International Journal of Quality and Reliability Management, 26*(4), 325-340. https://doi.org/10.1108/02656710910950333

Hadullo, K., Oboko, R., & Omwenga, E. (2017). A model for evaluating E-Learning systems quality in higher education in developing countries. *International Journal of Education and Development Using Information and Communication Technology, 13*(2), 185.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate data analysis* (6th ed.). Pearson Education.

Hair, J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (2010). *Multivariate data analysis* (7th ed.). Prentice Hall.

Harriman, G. (2004, March 23). *What is blended learning?*. E-Learning Resources. http://www.grayharriman.com/blended_learning.htm

Hoyle, R. H. (2011). *Structural equation modeling for social and personality psychology* (1st ed.). Sage.

Huang, C. Y., & Kao, Y. S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. *Mathematical Problems in Engineering, 1*, 1-23.

Huang, J., & Duangekanong, S. (2022). Factors Impacting the Usage Intention of Learning Management System in Higher Education. *AU-GSB E-JOURNAL, 15*(1), 41-51. https://doi.org/10.14456/augsbejr.2022.59

Kim, H., & Niehm, L. S. (2009). The impact of website quality on information quality, value, and loyalty intentions in apparel retailing. *Journal of Interactive Marketing, 23*(3), 221-233. https://doi.org/10.1016/j.intmar.2009.04.009

Kim, T. G., Lee, J. H., & Law, R. (2008). An empirical examination of the acceptance behaviors of hotel front office systems: an extended technology acceptance model. *Tourism Management, 29*(3), 500-513. https://doi.org/10.1016/j.tourman.2007.05.016

Kisanjara, S. B., Tossy, T. M., Sife, A. S., & Masanjila, S. S. (2019). E-Learning uptake among academicians and students. *International Online Journal of Education and Teaching, 6*(1), 18-35. https://doi.org/10.3991/ijet.v15i01.11349

Klem, L. (2000). *Structural equation modeling.* American Psychological Association.

Krishnasamy, S., Ling, L. S., & Kim, T. C. (2020). Improving learning experience of probability and statistics using multimedia system. *International Journal of Emerging Technologies in Learning (IJET), 15*(1), 77-87.

Kuo, Y. C., Walker, A. E., Schroder, K. E. E., & Belland, B. R. (2014). Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. *The Internet and Higher Education, 20(*1), 35-50. https://doi.org/10.1016/j.iheduc.2013.10.001

Lakhal, S., Khechine, H., & Pascot, D. (2013). Student behavioral intentions to use desktop video conferencing in a distance course: Integration of autonomy to the UTAUT model. *Journal of Computer in Higher Education, 25,* 93-121. doi:10.1007/s12528-013-9069-3

Lee, B. C., Yoon, J. O., & Lee, I. (2009). Learners' acceptance of e-learning in South Korea: theories and results. *Computers & Education, 53*(4), 1320-1329. https://doi.org/10.1016/j.compedu.2009.06.014

Lee, Y. C. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. *Bioinformatics, 31*(5), 517-541. https://doi.org/10.1108/14684520610706406

Liu, I. F., Chen, M. C., Sun, Y. S., Wible, D., & Kuo, C. H. (2010). Extending the TAM model to explore the factors that affect intention to use an online learning community. *Computers & Education, 54*(2), 600-610. https://doi.org/10.1016/j.compedu.2009.09.009

Lu, D. N., Le, H. Q., & Vu, T. H. (2020, June 20). *The factors affecting acceptance of e-learning: a machine learning algorithm approach.* https://files.eric.ed.gov/fulltext/EJ1272761.

Marandu, E. E., Mathew, I. R., Svotwa, T. D., Machera, R. P., & Jaiyeoba, O. (2023). Predicting students' intention to continue online learning post-COVID-19 pandemic: extension of the unified theory of acceptance and usage technology. *Journal of Applied Research in Higher Education, 15*(3), 681-697.

Mirabolghasemi, M., Shasti, R., & Choshaly, S. H. (2021). An investigation into the determinants of blended learning satisfaction from EFL learners' perspectives. *Interactive Technology and Smart Education, 18*(4), 391-408. https://doi.org/10.1108/ITSE-06-2021-0075.

Molinillo, S., Aguilar-Illescas, R., Anaya-Sanchez, R., & Vallespın-Aran, M. (2018). Exploring the impacts of interactions, social presence, and emotional engagement on active collaborative learning in a social web-based environment. *Computers and Education, 123*(8), 41-52. https://doi.org/10.1016/j.compedu.2018.04.012

Moorthy, K., Yee, T., T'ing, L., & Kumaran, V. (2019). Habit & hedonic motivation are the strongest influences in mobile learning behaviors among higher education students in Malaysia. *Aust J Educ Technol, 35*(4), 174-191. https://doi.org/10.14742/ajet.4432

Nguyen, T. D., Nguyen, D. T., & Cao, T. H. (2014). *Acceptance and use of information system: e-learning based on cloud computing in Vietnam* (1st ed.). Springer.

Okaz, A. (2015). Integrating blended learning in higher education. *Procedia - Social and Behavioral Sciences, 186,* 600-603. https://doi.org/10.1016/j.sbspro.2015.04.086

Ong, C. S., Lai, J. Y., & Wang, Y. S. (2004). Factors affecting engineers' acceptance of asynchronous e-learning systems in high-tech companies. *Information and Management, 41*, 795-804. https://doi.org/10.1016/j.im.2003.08.012

Owston, R., Wideman, H., Murphy, J., & Lupshenyuk, D. (2008). Blended teacher professional development: a synthesis of three program evaluations. *The Internet and Higher Education, 11*(3), 201-210. https://doi.org/10.1016/j.iheduc.2008.07.003

Ozkan, S., & Koseler, R. (2009). Multi-dimensional students' evaluation of e-learning systems in the higher education context: an empirical investigation. *Computers and Education, 53*(4), 1285-1296. https://doi.org/10.1016/j.compedu.2009.06.011

Pai, H. H., Sears, D. A., & Maeda, Y. (2015). Effects of small-group learning on transfer: a metanalysis. *Educational Psychology Review, 27*(1), 79-102. https://doi.org/10.1007/s10648-014-9260-8

Pallant, J. (2010). *SPSS survival manual: A step-by-step guide to data analysis using SPSS* (4th ed). McGraw Hill.

Passey, D. (2006). Technology enhancing: analyzing use of information and communication technology by primary and secondary school publish with learner's framework. *The curriculum journal, 16*(2), 139-166. https://doi.org/10.1080/09585170600792761

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40.

Perera, R., & Abeysekera, N. (2022). Factors affecting learners' perception of e-learning during the COVID-19 pandemic. *Asian Association of Open Universities, 17*(1), 84-100. https://doi.org/10.1108/aaouj-10-2021-0124

Pituch, K. A., & Lee, Y. K. (2006). The influence of system characteristics on e-learning use. *Computers & Education, 47*(2), 222-244.

Polites, G. L., Williams, C. K., Karahanna, E., & Seligman, L. (2012). A theoretical framework for consumer e-satisfaction and site stickiness: an evaluation in the context of online hotel reservations. *Journal of Organizational Computing and Electronic Commerce, 22*(1), 1-37. https://doi.org/10.1080/10919392.2012.642242

Raees, F. L. (2002). Applications and benefits of information technology. *Educational Technology, 2*, 16.

Ramayah, T., Ahmad, N. H., & Lo, M. C. (2010). The role of quality factors in intention to continue using an e-learning system in Malaysia. *Procedia-Social and Behavioral Sciences, 2*(2), 5422-5426. https://doi.org/10.1016/j.sbspro.2010.03.885

Rivera, J. L. (2019). Blended learning-effectiveness and application in teaching and learning foreign languages. *Open Journal of Modern Linguistics, 9*, 129-144. https://doi.org/10.4236/ojml.2019.92013

Rudhumbu, N. (2022). Applying the UTAUT2 to predict the acceptance of blended learning by university students. *Asian Association of Open Universities Journal, 17*(1), 15-36. https://doi.org/10.1108/AAOUJ-08-2021-0084

Rughoobur, S., & Hosanoo, Z. A. (2021). An evaluation of the impact of confinement on the quality of e-learning in higher education institutions. *Quality Assurance in Education, 29*(4), 422-444. https://doi.org/10.1108/qae-03-2021-0043

Samsudeen, S. N., & Mohamed, R. (2019). University students' intention to use e-learning systems. *Interactive Technology and Smart Education, 16*(3), 219-238. https://doi.org/10.1108/itse-11-2018-0092

Sattari, A., Abdekhoda, M., & Zarea, G. (2017). Determinant factors affecting web-based training acceptance by health students: Applying the UTAUT model. *International Journal of Emerging Technology and Learning, 12*(10), 112-126. https://doi.org/10.3991/ijet.v12i10.7421

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282-286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

Sharma, S. K., Gaur, A., Saddikuti, V., & Rastogi, A. (2017). Structural equation model (SEM)-neural network (NN) model for predicting quality determinants of e-learning management systems. *Behavior and Information Technology, 36*(10), 1053-1066. https://doi.org/10.1080/0144929x.2017.1340973

Shin, D. H. (2015). Effect of the customer experience on satisfaction with smartphones: assessing smart satisfaction index with partial least squares, *Telecommunications Policy, 39*(8), 627-641. https://doi.org/10.1016/j.telpol.2014.10.001

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M.A. Lange (Ed.), *Leading Edge Psychological Tests and Testing Research* (pp. 27-50). Nova.

Singh, H. (2003). Building effective blended learning programs. *Educational Technology, 43*(6), 51-54. https://doi.org/10.4018/978-1-7998-7607-6.ch002

Soper, D. (2006). *Calculator: A-priori Sample Size for Structural Equation Models. Daniel Soper.* https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Stahl, G., Koschmann, T., & Suthers, D. (2006). Computer-supported collaborative learning: an historical perspective. In Sawyer, R. K. (Ed.), *Cambridge Handbook of the Learning Sciences* (pp. 409-426). Cambridge University Press. https://doi.org/10.1017/9781108888295.025

Strau, S., & Rummel, N. (2020). Promoting interaction in online distance education: designing, implementing, and supporting collaborative learning. *Information and Learning Sciences, 121*(5/6), 251-260. https://doi.org/10.1108/ILS-04-2020-0090

Straub, D. W. (1989). Validating instruments in MIS research. *MIS Quarterly, 13*(2), 147-169. https://doi.org/10.2307/248922

Sun, P. C., Tsai, R. J., Finger, G., Chen, Y. Y., & Yeh, D. (2008). What drives a successful e-learning? An empirical investigation of the critical factors influencing learner satisfaction. *Computers & Education, 50*(4), 1183-1202.

Tajuddin, R. A., Baharudin, M., & Hoon, T. S. (2013). System quality and its influence on students' learning satisfaction in UiTM Shah Alam. *Procedia - Social and Behavioral Sciences, 90*, 677-685. https://doi.org/10.1016/j.sbspro.2013.07.140

Twum, D., Smith, J., & Brown, L. (2022). Exploring new trends in digital education. *Journal of Educational Technology, 35*(3), 45-60. https://doi.org/10.1016/j.jedutech.2022.05.007

Venkatesh, V., & Davis, F. (2000). A theoretical extension of the technology acceptance model: four longitudinal field studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: development and test. *Decision Sciences, 27*(3), 451-481. https://doi.org/10.1111/j.1540-5915.1996.tb00860.x

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Wang, J. (2019). Application of blending learning based on network learning space in teaching design of digital art. *International Journal of Educational Technology, 14*(9), 177-189. https://doi.org/10.3991/ijet.v14i03.10107

Wang, Q. (2008). A generic model for guiding the integration of ICT in to teaching and learning. *Innovation Education and Teaching International, 45*(4), 411-419. https://doi.org/10.1080/14703290802377307

Wang, W. T., & Wang, C. C. (2009). An empirical study of instructor adoption of web-based learning systems. *Computers and Education, 53*(3), 761-774. https://doi.org/10.1016/j.compedu.2009.02.021

Wong, L., Tatnall, A., & Burgess, S. (2014). A framework for investigating blended learning effectiveness. *Education Training, 56*(2/3), 233-251. https://doi.org/10.1108/et-04-2013-0049

Wu, J., & Liu, W. (2013). An empirical investigation of the critical factors affecting students' satisfaction in EFL blended learning. *Journal of Language Teaching Research, 4*(1), 176-185. https://doi.org/10.4304/jltr.4.1.176-185

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information and Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Yiong, B. L. C., Sam, H. K., & Wah, T. K. (2008). *Acceptance of e-learning among distance learners: a Malaysian perspective* (1st ed.). Australasian Society for Computers in Learning in Tertiary Education.

Zhang, S., Zhao, J., & Tan, W. (2008). Extending TAM for online learning systems: An intrinsic motivation perspective. *Tsinghua Science & Technology, 13*(3), 312-317. https://doi.org/10.1016/s1007-0214(08)70050-6